Contents lists available at ScienceDirect

Journal of Affective Disorders

journal homepage: www.elsevier.com

Disrupted latent decision processes in medication-free pediatric OCD patients

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ARTICLE INFO

Article history:
Received 3 June 2016
Received in revised form 14 September 2016
Accepted 18 September 2016
Available online xxx

Keywords:
Decision making
Hierarchical Drift Diffusion Model
Obsessive Compulsive Disorder
Children

ABSTRACT

Background
Decision-making in Obsessive Compulsive Disorder has typically been investigated in the adult population. Computational approaches have recently started to get integrated into these studies. However, decision-making research in pediatric OCD populations is scarce.
Methods
We investigated latent decision processes in 21 medication-free pediatric OCD patients and 23 healthy control participants. We hypothesized that OCD patients would be more cautious and less efficient in evidence accumulation than controls in a two alternative forced choice (2AFC) task.
Results
Pediatric OCD patients were less efficient than controls in accumulating perceptual evidence and showed a tendency to be more cautious. In comparison to post-correct decisions, OCD patients increased decision thresholds after erroneous decisions, whereas healthy controls decreased decision thresholds. These changes were coupled with weaker evidence accumulation after errors in both groups.
Limitations
The small sample size limited the power of the study.
Conclusions
Our results demonstrate poorer decision-making performance in pediatric OCD patients at the level of latent processes, specifically in terms of evidence accumulation.

1. Introduction

OCD is a debilitating psychiatric condition with the age of onset spanning a range from early childhood to adulthood (Pauls et al., 2014). OCD affects 1–3% of the pediatric/adolescent population (Valleni-Basile et al., 1994; Pauls et al., 1995; Apter et al., 1996). The condition includes either or both obsessions and compulsions (American Psychiatric Association, 2013), which significantly reduce the quality of the patients' lives.

A number of previous studies have investigated decision-making in adult OCD patients. However there is less research conducted with pediatric OCD populations. The Iowa Gambling Task (IGT; Bechara et al., 1994) has been used in many studies with adult OCD patients. Some studies revealed that OCD patients made more disadvantageous choices (e.g. Cavedini et al., 2002; Rocha et al., 2011; Starcke et al., 2010), however other studies revealed comparable performance to healthy controls (e.g. Nielen et al., 2002; Lawrence et al., 2006). In the only IGT study conducted with pediatric OCD patients (n_{OCD}=22; $n_{Control}$=22), Kodaira et al. (2012) found more disadvantageous responding of participants with OCD on the last block of testing and suggested that pediatric OCD patients had impaired decision-making. It is worthy to note that recruiting medication-free OCD patients is challenging and that some patients in the above mentioned studies were on psychiatric medications at the time of the experiment (e.g. Kodaira et al., 2012; Lawrence et al., 2006; Rocha et al., 2011; Starcke et al., 2010).

Much neuropsychological research has been undertaken in adult OCD groups but with highly divergent outcomes (Abramovitch et al., 2013a). A recent meta-analysis with 115 studies revealed an average moderate effect size across domains denoting worse performance for OCD patients, which the authors conclude might not allude to clinical significance (Abramovitch et al., 2013a). There is much less neuropsychological research conducted with pediatric OCD patients. A recent meta-analysis compiling 11 studies investigating executive function, memory, processing speed, visuospatial abilities, and working memory has concluded that there is no evidence for neuropsychological dysfunction in pediatric OCD populations (Abramovitch et al., 2015). This meta-analysis did find a trend for worse performance

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http://dx.doi.org/10.1016/j.jad.2016.09.011
0165-0327/

in neuropsychological tasks for pediatric OCD patients compared to healthy controls, but the effect sizes were neither statistically nor clinically significant. The authors attributed the lack of statistical significance to the number of available studies and sample sizes across studies, and pointed to a need for further research. Importantly, decision making tasks were not included in the meta-analysis.

In their critical review, Abramovitch and Cooperman (2015) argue that neuropsychological tests, although informative for the psychiatric area, can be improved with some modifications. For instance, because many neuropsychological studies employ commonly used classic experimental procedures and analyses rather than venturing to new methods, the conclusions may become restricted and thereby uninformative. With different approaches in analyses and changes in the established neuropsychological tasks (e.g. adding distractors or manipulating the task load) (Abramovitch and Cooperman, 2015), the area can benefit from more in-depth characterization of behavior.

In the area of computational psychiatry, researchers are also striving to come up with more in depth analyses of psychiatric problems and shift from a symptom-based descriptive understanding of psychiatric disorders to descriptions involving "objective computational multidimensional functional variables" (Wiecki et al., 2015, p. 378). To this end, Wiecki et al. (2015) point to sequential sampling models as important tools for the field of psychiatry. Drift diffusion model (DDM) is a prominent sequential sampling model, which utilizes a combination of accuracy and reaction time data to explain latent decision-making processes (Ratcliff, 1978; Ratcliff and McKoon, 2008; Ratcliff and Rouder, 1998). Through these processes, the model can provide psychological explanations (such as cautious responding, non-decision time, biases in decision-making and evidence accumulation efficiency) to differences in choice behavior (White et al., 2010a).

The DDM assumes that in a decision-making task with two choices, the agent starts at a point (starting point: z; initial belief state) between the two alternatives and accumulates evidence from the noisy signal with some (drift rate: v). As the agent gathers enough evidence to reach one of the thresholds, the corresponding decision is made. The area between the thresholds associated with two alternatives is referred to as the boundary separation (e.g. Ratcliff and McKoon, 2008). The core parameters of DDM are threshold setting (a), drift rate (v), starting point (z), and non-decision time (Ter). The more complex version of the model (extended model; Ratcliff and Rouder, 1998) includes variabilities in non-decision time (St), drift rate (eta), and starting point (Sz). Threshold setting indexes speed accuracy tradeoff or the caution with which the decision is made; the higher the threshold setting the more caution the decision maker exercises. Drift rate indexes the rate of evidence accumulation or signal to noise ratio. The starting point indexes the bias towards either of the two choices and the non-decision time indexes the duration of signal detection or motor response (e.g. Ratcliff and McKoon, 2008; White et al., 2010a).

White et al. (2010a) have pointed out the benefits of using DDM in clinical research. In support of this argument, the DDM has indeed been successfully used in studies with populations suffering from ADHD (e.g. Karalunas and Huang-Pollock, 2013; Metin et al., 2013; Mulder et al., 2010), anxiety (White et al., 2010b), depression (Pe et al., 2013), and clinical (Banca et al., 2015) and subclinical (Erhan and Balcı, 2015) OCD.

Banca et al. (2015) used the dot motion discrimination task with three different levels of signal to noise ratios (SNRs) to study decision-making behaviors of mostly medicated adult OCD patients (n_{OCD}=28; $n_{Control}$=35). Monetary rewards and punishments indicated the correct and incorrect responses. Performances on low (coherences .025 and .05), medium (coherences .15 and .25), and high (coherences .45 and .7) levels of SNRs were compared using Hierarchical Drift Diffusion Model (HDDM). The findings revealed higher threshold settings for OCD patients than healthy controls at low and medium SNR levels and lower drift rates than healthy controls in medium and high SNR levels. In other words, OCD patients responded in a more cautious manner and gathered more evidence than controls in lower SNR but accumulated evidence less efficiently in higher SNR scenarios.

Erhan and Balcı (2015) also used the dot motion discrimination task but with a single coherence level (12%) and with healthy adult participants (N=74) who rank on various levels on OCD scales. Their findings revealed that increases in rumination and checking tendencies as well as an increase in the entire OC score predicted higher threshold settings. Differing from the clinical OCD study (Banca et al., 2015) subclinical OC traits did not predict drift rates. Authors concluded that a low drift rate could be a signature for clinical OCD populations.

In the current study, we seek to understand the latent decision variables of a medication-free pediatric OCD population (ages 9–16). Even though symptom dimensions of OCD are alike across age groups, pediatric and adult OCD populations seem to have abnormal neural activations in similar brain locations but in reversed directions (Gilbert et al., 2009). Abramovitch et al. (2012), in their review on neuroimaging in pediatric OCD, also argued that adult OCD and pediatric OCD can be distinct and that neurodevelopmental factors such as pruning and myelination make it more difficult to pinpoint a common neurobiological basis for OCD across ages.

We sought to fill the empirical gap in the literature regarding the study of decision-making in the pediatric OCD group at the level of latent processes. We hypothesized that pediatric OCD patients, similar to adult OCD patients (Banca et al., 2015) would set higher decision thresholds than control participants due to the checking and doubting nature of the disorder. Based on the argument that sensory-perceptual evidence, which lets most people make rapid decisions, is not sufficient for patients with OCD (Sachdev and Malhi, 2005), we hypothesized that these patients would need higher amounts of evidence before making a decision. We also predicted lower drift rates on the part of OCD patients as an alternative basis for decision-making deficits associated with this group. As an extension of these predictions, we also predicted OCD patients to set higher thresholds after errors compared to after correct responses.

2. Methods

2.1. Participants

Fifty-three participants partook in the study. Participants with OCD diagnosis (n=21) were recruited from the pediatric clinic of a public psychiatric hospital, İstanbul Erenköy Psychiatric Training and Research Hospital. The participants in the control group (n=32) were volunteers from a public school in a nearby neighborhood. The study was approved by the Koc University and Erenköy Psychiatric Training and Research Hospital Ethical Review Boards and related permissions were obtained from the Istanbul Provincial Directorate of National Education Board. All parents signed informed consent forms and all participants gave assent to partake in the study. Subjects were compensated by a fixed amount for participation-related expenses (e.g. travel).

The exclusion criteria for both groups were intellectual disability, major neurological disorders, and use of psychiatric medication within the last 6 months. The inclusion criterion for the clinical par-

ticipants was an OCD diagnosis by the primary psychiatrist with no comorbid psychiatric disorders. Patients participated in the study immediately after the initial diagnosis without having started medication, thus, their treatment schedule was not delayed.

Inclusion criteria for control participants was the absence of current clinical diagnosis, assessed by The Development and Well-Being Assessment (DAWBA) (Goodman et al., 2000; Dursun et al., 2013) (i.e. less than 3 points in all computer assigned diagnostic criteria). For stringency, presence of any psychiatric symptom was a reason for exclusion from the control group, even if the symptoms did not amount to a full clinical diagnosis. The symptoms for exclusion were ascertained by the psychiatrists in our group, who personally assessed the DAWBA results in addition to the computerized system. Seven participants were removed for having psychiatric symptoms (note that the inclusion of these participants in the control group, overall, led to similar findings). An additional two participants were removed because their parents did not complete the DAWBA. The final control group was composed of 23 participants.

2.2. Procedure

All participants completed the Dot Motion Discrimination Task and the block design and vocabulary subsections of Wechsler Intelligence Scale for Children Revised, in Turkish (WISC-R; Wechsler, 1974; Savasir and Sahin, 1995). The children in the clinical group were also administered the CY-BOCS (Scahill et al., 1997; Yucelen et al., 2006). All parents in both patient and control groups filled the socio economic status forms and completed the DAWBA Interview for Parents with the researcher's instructions. Participants were also provided passwords for DAWBA and were asked to complete it in their own time.

DAWBA is a valid computerized diagnostic package formed of various scales and open-ended questions (Goodman et al., 2000). The Turkish translation and validation of this tool has been undertaken by Dursun et al. (2013). The interrater reliability score in Dursun et al. (2013) was shown to be excellent and the validity score to be good to excellent. CY-BOCS is a valid and reliable 10-item semi-structured clinical interview to measure the severity of OCD symptoms in children and adolescents (Scahill et al., 1997). The Turkish version demonstrates good interrater reliability scores and researchers report that the translated CY-BOCS can be used in clinical research settings (Yucelen et al., 2006).

2.3. Dot motion discrimination task

Dot motion discrimination task (DMDT) is a commonly used visual perceptual decision-making task with several adjustable parameters. In the current study, white dots appeared in a circular space with a diameter of 3 in. in the middle of a black screen. While some percentage of the dots (12%) moved cohesively to either right or left, the rest of the dots were displaced randomly within the circular space. Response to stimulus intervals (M=2 s) were sampled from a truncated exponential distribution with a 1 s lower bound. The task was to identify to which direction the dots were moving and press the corresponding keys. The correct responses were followed by a beep sound and were worth one point each. The incorrect responses neither had feedback nor penalty. On every 10th response total points earned appeared on the screen. The experiment was run on MATLAB, using the SnowDots (2012) developed at the University of Pennsylvania by Joshua Gold.

Each session was formed of a practice session of 2 min, followed by a free response session of 24 min (8 blocks of 3 min) and a signal detection session of 3 min. Different than the first two sessions, in the signal detection session, participants were asked to press the corresponding keys immediately as they saw the dots emerge on the screen, with no consideration for direction of movement. In all sessions a buzzing sound followed all anticipatory responses (RT <100 ms), which were penalized with 1 s timeout. Participants were told to accumulate as many points as possible.

3. Data analysis

We used both Bayesian and frequentist independent samples t-tests to check if the clinical and control group were comparable with regards to age and IQ levels. The difference between accuracy, reaction times and signal detection times between the clinical and control group were also assessed by independent samples t-tests.

HDDM (Wiecki et al., 2013) was fit to the response times (RT) and choices (correct-incorrect) using the software developed by Wiecki et al. (2013) (http://ski.clps.brown.edu/hddm_docs/). Our model allowed for changes in both drift rate and threshold setting. On all models we drew 5000 posterior samples using the Markov Chain Monte Carlo (MCMC) algorithm discarding first 20 as burn-in. Wiecki et al. (2013) suggest mixture models, where a certain percentage of trials are outliers that come from a uniform distribution and are generated by processes other than the DDM. We set the outlier ratio to be 1% for the between-subject models and 5% for the within-subject models. To assess model convergence, we visually observed the trace, the autocorrelation, and the marginal posterior. To assess individual fit qualities we visually inspected the posterior predictions. To test our hypotheses for the models, we compared the posterior probabilities of parameters, which leads to a Bayesian probability measure (P). The P value is the probability that one variable's estimate is larger than that of the other, based on their posterior probability distributions.

We used paired samples t-tests to compare post-error and post-correct trials in terms of reaction times (PES; post error slowing) as well as accuracy. A within-subjects HDDM was fit to post error and post correct responses for each group (e.g. Dutilh et al., 2012), allowing both drift rate and threshold setting to vary.

4. Results

The ages were matched for the clinical (M=12.00, SD=1.90) and control (M=12.46, SD=1.14) groups (t(32.15)=.98, p=.34, BF_{01}=2.25). The vocabulary (v) and block design (b) subtests of the WISC-R were also matched for the clinical (M_v=11.55, SD_v=2.09; M_b=12.00, SD_b=3.42) and control (M_v=12.00, SD_v=1.41; M_b=13.61, SD_b=3.43) groups (t(32.68)=.81, p_v=.42, BF_{01}=2.51; t(42)=1.56, p_b=.13, BF_{01}=1.28). In the clinical group one participant could not complete the vocabulary subtest due to time constraints. Of the included participants, all parents completed DAWBAs. In the clinical group out of 21 participants, 12 completed and 4 partially completed the DAWBAs. In the control group out of 30 participants, 16 completed and 1 partially completed the DAWBAs.

Paired samples t-test scores revealed that both the control and clinical group had post-error slowing. In the control group, participants responded faster after correct (M=1.44 s, SD=.49 s) than after incorrect trials (M=1.65 s, SD=.77 s), t(22)=2.52, p=.02. Same was true for the clinical group such that participants responded faster after correct trials (M=1.78 s, SD=.64 s) than they did after incorrect trials (M=2.24 s, SD=1.08 s), t(20)=2.32, p=.03.

Paired samples t-tests also revealed that accuracy after correct responses was higher than accuracy after error responses for both

groups. In the clinical group post correct accuracy (M=.74, SD=.10) was higher than post error accuracy (M=.62, SD=.08), $t(20)$=7.78, p<.001. In the control group as well, post correct accuracy (M=.79, SD=.13) was higher than post error accuracy (M=.71, SD=.12), $t(22)$=6.25, p<.001.

Overall the control group (M=1.48 s, SD=.55 s) had faster reaction times than the clinical (M=1.91 s, SD=.72 s) group, $t(42)$=2.26, p=.03, BF_{01}=.46. The clinical (M=.71, SD=.10) and control (M=.78, SD=.14) groups did not differ in their accuracy ($t(42)$=1.82, p=.08, BF_{01}=.91). Signal detection times for the control (M=.40 s, SD=.06 s) and clinical (M=.41 s, SD=.10 s) groups did not differ ($t(42)$=.45, p=.65, BF_{01}=3.09).

HDDM analyses comparing the two groups revealed that OCD patients had lower drift rates than controls (P=.99). Moreover, a tendency for higher threshold settings was observed in the clinical group (P=.93). The within subject HDDM analyses revealed that the post error responses had lower drift rates than the post correct responses for both the clinical (P=1.0) and control group (P=1.0). However a difference between the groups emerged in terms of post-error threshold setting. The post error responses had higher threshold settings than the post correct responses for the clinical group (P=1.0) whereas the post error responses had lower threshold settings than the post correct responses for the control group, (P=1.0).

5. Discussion

We investigated the latent decision-making processes of a pediatric OCD sample in comparison to a healthy control sample in a two alternative forced choice task using HDDM. We hypothesized that OCD patients would have higher threshold settings and lower drift rates than control participants. We also predicted that OCD patients would set higher thresholds after errors compared to after correct responses. Our findings provided support for our predictions: OCD patients displayed lower drift rates and showed a strong tendency for higher threshold settings than healthy controls. The patients may have compensated their lower evidence accumulation efficiency (drift rate) with increased caution, possibly explaining their slower RTs but comparable error rates with the healthy control group.

These results are in support of the findings of the recent clinical OCD study (Banca et al., 2015) and in partial support of the findings of the subclinical OC study (Erhan and Balcı, 2015). The subclinical OC study found that higher total OC scores and higher rumination and checking scores predicted higher threshold settings, with no relationship between OC scores and drift rates. The clinical study (Banca et al., 2015) on the other hand found that patients with OCD had both higher threshold settings and lower drift rates than the healthy controls in medium SNR conditions (which best represents the SNR used here). In the current study, we found lower drift rates for OCD patients with a tendency for higher threshold settings. Taken together these findings indicate that lower drift rates might be a signature of clinical OCD as was originally suggested by Erhan and Balci (2015).

The threshold setting differences in the pediatric OCD group vs. the healthy controls are not as distinct as those reported by Banca et al. (2015) for adults. According to recent approaches that rely on signal detection theory, it is reasonable to be more cautious when signal detection capacity is low (akin to walking slower and more cautiously (e.g. higher threshold setting) in a dimly lit room (e.g. low drift rate)) (Lynn and Barrett, 2014). One reason why the pediatric population does not show as increased a caution despite low drift rates, as adults do, could be the differences in used coping responses possibly due to age (Aldwin, 1994). Overall, people with high OC traits have low distress tolerance (e.g. Blakey et al., 2015); however adults might have compensated with better emotion regulation and coping strategies. We did not originally incorporate emotion regulation or distress tolerance into our interpretation of the decision-making behavior. However, emotions have been argued to effect decisions strongly (Lerner et al., 2015), and changing emotional reactions through emotion regulation strategies also change decisions (Phelps et al., 2014). Future studies can focus on the relations of emotion regulation with latent decision variables.

Our findings regarding the post correct and post error behaviors indicate that both groups have lower drift rates while responding after errors than when they do after correct trials. Moreover, in line with our hypothesis, OCD patients have higher threshold settings responding after errors than after correct trials. Interestingly, this pattern is reversed in the healthy control participants for whom threshold settings are lower in the post error trials than post correct trials. Our findings are very similar to those of White et al. (2010a)'s study, in which participants with high and low anxiety scores performed a recognition memory task. Akin to our study, highly anxious participants had significantly increased threshold settings after errors whereas participants with lower anxiety scores had reduced (although non-significant) post error thresholds. White et al. (2010a) also found that after errors, discriminability (difference in drift rate of familiar and novel stimuli) decreased for both groups. Although they worked with students with high and low anxiety scores, our findings with a clinical pediatric population are highly comparable.

Results in our study are however different than Dutilh et al. (2012)'s findings, which suggest that post error slowing almost solely results from an increase in threshold settings after errors. What we find across groups, a decrease in drift rates, point to a dampened evidence accumulation efficiency, possibly due to distraction (Dutilh et al., 2012). This difference in the explanation of post error slowing at the level of latent processes could be due to age, and can benefit from more research.

The symptomatology of OCD as put forth in DSM-V (American Psychiatric Association, 2013) matches with the observed latent variables. Time-consuming obsessions, compulsions, and efforts to suppress them behaviorally manifest as inattention and distraction in individuals with OCD (Abramovitch et al., 2013b). This is also what our outcome in terms of latent variables show. The pediatric OCD group was found to be less efficient in accumulating evidence compared to healthy controls, possibly indicating that they were distracted and less attentive to the stimuli. Although OCD patients would also be expected to require more evidence before making a decision (higher threshold) based on DSM-V's characterization of this disorder (e.g. checking), albeit strong, this was only a trend in the data.

Moreover, the proposed neural correlates of drift rate and threshold settings match with the proposed neural correlates of OCD. The frontoparietal (e.g. de Vries et al., 2014; Melloni et al., 2012) and corticostriatal pathways (e.g. Burguiere et al., 2015) are implicated in OCD. Similar neurobiological mechanisms have been implicated for drift rate and decision threshold. For instance, in a recent review Mulder et al. (2014) concluded that threshold settings are associated with activations in the frontobasal ganglia network and changes in drift rates are associated with activations in frontoparietal network.

5.1. Limitations

The relatively low number of participants is a limitation of this study, preventing investigation of within-group effects due to factors such as age. In order to assure a healthy and homogenous control group devoid of any psychiatric symptoms, we further reduced the

sample size of our control group from 30 to 23. The sample size of our OCD group was limited as we excluded patients with medication use and comorbidities. However, the smaller sample sizes were compensated by the homogeneity of the groups, which decreases the possibility of confounds and within-group variability, and bolsters the validity of our inferences regarding the corresponding populations. Another limitation is the lack of a structured diagnostic assessment tool for the OCD group. However, the lack of such assessment tool was compensated with the diagnostic clinical experience of the assessing psychiatrist.

6. Conclusion

Our study revealed that pediatric OCD patients have lowered evidence accumulation efficiency and a trend in increased caution, in comparison to healthy controls. Moreover, while errors cause distraction in the subsequent trial for both groups, the two groups react differently in terms of caution; OCD patients become more cautious after they make an error whereas healthy controls become less cautious. Our findings add to a series of studies that emphasize the importance of computational decision-theoretic approaches for characterizing latent processes in the study of clinical populations. By investigating the latent processes through HDDM, we were able to identify differences that match the symptomatology and neurobiology of OCD and were not evident in the isolated analysis of the reaction time and accuracy data. We also observed indications that comparing latent processes may reveal a signature that sets clinical OCD apart from high OC traits alone. The minor differences between our findings with a pediatric population and those of studies with adult populations point to a need for further research that incorporates development and emotion regulation into studies of latent processes in decision-making.

Acknowledgements

We would like to thank Hakan Karşılar for his help on the DMDT code; Elif Akın for her help in recruiting participants; Aysu Hazar for her help with data collection.

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